# SOURCES OF ICT SPILLOVERS, ABSORPTIVE CAPACITY AND PRODUCTIVITY PERFORMANCE

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## Abstract

Using company account data for the US we analyse the spillover impact of industry ICT on productivity performance in the uptake of the new technology. We use different definitions of spillovers to account for inter- and intra-industry spillover effects and document that firm's absorptive capacity is a crucial factor to exploit the external benefits generated by the new digital technologies. Contrary to existing evidence based on industry data, our results corroborate the presence of ICT spillovers in the US economy at company level, even when we consider a wide array of control factors and model mis-specifications.

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#### Introduction

Advances in the field of information and communication technologies (ICT) have driven a new technological revolution that has modified not only the ways of doing business but also the way to perform daily household activities. Due to its widespread applications, ICT has been classified as a General Purpose Technology (GPT), exactly like electrification and other great inventions of the past (Jovanovic and Rousseau 2005). As a GPT, ICT is characterized by considerable technological progress, a pervasive use in a wide range of economic sectors, as well as by the ability to boost complementary innovations and to generate spillover effects (Bresnahan and Trajtenberg, 1995, Lipsey et al. 2005). These characteristics have produced positive productivity effects throughout the economy (Jovanovic and Rousseau, 2005, O'Mahony and Vecchi 2005, Venturini, 2009). ICT is now recognised as an important determinant of productivity growth especially if coupled with investments in other intangible assets such as R&D, organizational and human capital (Brynjolfsson and Hitt 2000, 2003).

However, while the direct impact of ICT on productivity is well documented, it is still unclear whether ICT generates positive spillovers as the empirical evidence so far has been rather weak. While some studies find significant effects (van Leeuwen and van der Wiel 2003, Severgnini 2011, Venturini, 2011), others strongly reject the existence of spillovers (Stiroh 2002, Acharya and Basu 2010, Haskel and Wallis 2010, Van Reenen et al. 2010, Moshiri and Simpson 2011). This mixed set of results has lead researchers to doubt the importance of the GPT effects related to ICT (Draca et al. 2007) and has prevented, particularly within Europe, the formulation of appropriate policies aimed to facilitate the absorption and diffusion of new technologies.

The majority of studies that fail to find a positive ICT spillover effect are based on industry or economy wide data. It is therefore possible that the lack of a spillover effect from ICT is the result of an aggregation effect<sup>1</sup>. Here we use company level data to reassess the evidence on ICT spillovers and to understand their role in the US productivity revival of the 1990s. Our analysis of spillovers begins with a traditional approach which consists of modelling the output of a single firm as a function of its own inputs and an index of aggregate activity (Helpman 1984, Caballero and Lyons 1989, 1990, Vecchi 2000). Similarly to Jones (1968), we assume that spillovers or external economies are related to the scale of the industry ICT input and are external to the decisions taken by any firm so as to retain the perfectly competitive

<sup>&</sup>lt;sup>1</sup> Bryonjolfsson and Hitt (2000) discuss how aggregation effect cause a downward bias in the evaluation of the returns to ICT. A similar downward bias could affect the assessment of the spillover effect. Haskel and Wallis (2010) discuss this issue in relation to lack of evidence of ICT spillovers and R&D spillover in their study based on country-level data.

nature of the model. Therefore, we first evaluate whether companies' productivity performance is affected by the total stock of ICT capital within each industry. However, such *intra industry* effect might only provide a partial assessment of the role of aggregate ICT as it does not account for the possibility of spillovers across industries. In fact, companies can benefit from the adoption of ICT by upstream and downstream industries, via, for example, improved service provisions (financial and shipping services). A central issue of this paper is to capture these additional effects by means of a weighted ICT industry variable, where the weights are represented by input-output coefficients. This methodology based on inter-industry intermediate transactions is not new to the analysis of R&D spillover (Mun and Nadiri 2002, Wolff 2011) but, to our knowledge, it has not been use for constructing ICT spillover proxies.

In a context where technological knowledge and business practices diffuse rapidly, the capacity to exploit new sources of productivity growth appears crucial to compete in the global market. We focus on the 1990s as we intend to look at the uptake of the digital economy, when firm heterogeneity is large and first-movers gain productivity benefits which may cumulate over time. Additionally, in this period of time, the US experienced R&D boom, particularly in high-tech sectors (Brown et al. 2009) and this could have complemented the adoption and diffusion of ICT. Hence, we will directly test the hypothesis of whether firms' investments in R&D contribute to productivity by facilitating the absorption of ICT spillovers, particularly in the initial breakthrough of innovation.

The GPT literature claims that ICT spurs further innovation over time in a wide range of industries, ultimately boosting growth in TFP. This process takes time as the technology needs to be efficiently implemented within the production process. During this time, productivity can temporarily decrease (Hornstein and Krusell 1996, Aghion 2002). Only at a later stage firms will enjoy the benefits of their investment efforts. Given this lagged impact of ICT on productivity, spillovers are also likely to be characterised by a lag, although this aspect has been scarcely explored in the existing literature (Basu et al., 2003). By comparing contemporaneous as well as lagged effects we can achieve a better understanding of the relationship between ICT spillovers and productivity performance.

Our results show that ICT spillovers have played an important role in determining companies' productivity performance, but while intra industry spillovers have a contemporaneous negative effect, inter industry spillovers are positive and significant both in the short and in the long run. Our estimates suggest that it takes approximately 5 years for intra industry spillovers to positively affect productivity performance. Additionally, in the short run, companies'

innovative effort is complementary to ICT spillovers, but such complementarity disappears over time, with a more pervasive adoption and diffusion of the technology.

The following section presents an overview of the existing empirical evidence on the impact of spillovers on productivity (section 2), discussing the main implications of ICT as a General Purpose Technology (GPT) and as a potential source of spillovers. Section 3 presents the model used in the empirical analysis and describes the data sources. Our econometric findings are shown and discussed in sections 4 and 5. Section 6 concludes the paper.

#### 2. ICT as a General Purpose Technology and a source of spillovers

Advances in general purpose technologies (GPT) can potentially generate important productivity spillovers, i.e. increases in productivity in addition to the contribution of capital deepening. Assessing the importance of such spillovers can provide economists and policy makers the right measures to foster long run growth (Bresnahan1986). Hence there have been several attempts at describing possible channels through which spillovers can affect productivity performance. A considerable effort has been directed over time to the analysis of R&D or knowledge spillovers (Jaffe 1996, Griffith et al 2006, O'Mahony and Vecchi 2009) and a similar analytical framework has recently been extended to the analysis of spillovers from ICT (Stiroh 2002). In fact, as a GPT, ICT reconciles several explanations of knowledge spillovers. For example the re-organisation of the production process within firms, fostered by computerization, can be considered the result of learning-by-doing: the more firms invest in ICT, the more they learn about their potential applications which makes it possible to reorganise production in a more efficient way. ICT is also a source of 'pecuniary spillovers' (Griliches 1990)<sup>2</sup> as the combination of competition and innovation in the ICT producing sector has allowed computer-using industries to benefit from lower costs (Jorgenson, 2001). This source of spillover from the upstream to the downstream sector is also referred to as vertical externality (Bresnahan 1986). Next to this vertical externality we can also identify a horizontal externality, related to the sharing of the GPT among a large number of sectors. This links 'the interests of players in different application sectors, and is an immediate consequence of generality of purpose' (Bresnahan and Trajtemberg 1995).

Another source of spillovers is the increased efficiency of transactions among firms using ICT technology. Rowlatt (2001) and Criscuolo and Waldron (2003) argue that the use of electronic data interchange, internet-based procurement systems and other inter-organisational information systems produce a reduction in administrative costs, search costs, and better supply chain management. Atrostic and Nguyen (2005) find evidence for the US manufacturing of this "network externality" that arises when the efficiency of products or services increases as they are adopted by more users. Aghion (2002) defines as social learning this process of firms' learning about the implementation of a new technology from the experience of other firms in a similar situation. Brynjolfsson and Hitt (2002) present some case studies showing how ICT makes it possible for firms to interact with others in a faster and more efficient way. Electronic transfer of payment and invoices, automated inventory replenishment, on-line markets for

 $<sup>^{2}</sup>$  Griliches (1990) does not consider this type of spillovers as proper knowledge spillover but rather as the result of an incorrect measure of capital equipment, materials and their prices.

placing and receiving orders have all improved efficiency and consumers have benefited from increasing product variety and convenience.

The possibilities for ICT spillovers are numerous and can affect companies' performance at different stages of the production process; however, the empirical analysis so far has only provided a weak evidence of such positive externality. While some studies find significant effects (van Leeuwen and van der Wiel 2003, Severgnini 2011, Venturini 2011), others strongly reject the existence of spillovers (Stiroh 2002, Acharya and Basu 2010, Van Reenen et al. 2010, Moshiri and Simpson 2011). Stiroh (2002) regresses TFP growth on ICT capital and other controls for the US manufacturing sector over the period 1984-1999. He finds no evidence of ICT capital spillovers, nor evidence of spillovers from individual components (computer capital and telecommunication capital)<sup>3</sup>. Haskel and Wallis (2010), using aggregate data for the UK, find no evidence of spillovers from software assets, nor from other intangible assets such as economic competencies and R&D. Similarly Acharya and Basu (2010), fail to find positive ICT spillovers in a industry-level analysis for 16 OECD countries, but they do find significant spillover effects of domestic and foreign R&D investment.

A possible reason for these results lie in the type of data used in the empirical analysis, with micro data being generally more supportive of the spillover hypothesis compared to industry data<sup>4</sup>. This possibility was recognized by Brynjolfsson and Hitt (2000) and, more recently, by Haskel and Wallis (2010). Firm level studies seem to support this observation. For example, Van Leeuwen and van der Wiel (2003), using a sample of Dutch companies operating in market services, find a positive and significant ICT spillover on labour productivity. In their analysis the introduction of the spillover proxy reduces the size of own firm ICT capital stock, indicating that a considerable part of the ICT impact on labour productivity derives from spillovers. Similarly, Severgnini (2010) finds evidence of positive ICT spillovers in a sample of Italian manufacturing firms. He also notes that, compared to R&D, ICT can generate spillovers in an unlimited geographical space.

<sup>&</sup>lt;sup>3</sup> Stiroh's (2002) results could be explained by the fact that the study is carried out for manufacturing industries which are not the most ICT intensive industries. There is substantial evidence that the service sector is a heavy user of the new technology and it has played an important role in the US productivity resurgence (Inklaar et al. 2008). Focusing solely on manufacturing industries could results in a diminished effect for ICT spillovers.

<sup>&</sup>lt;sup>4</sup> An exception to this pattern of results is Venturini (2011), where using national data for 15 OECD countries, the authors finds evidence of positive ICT spillover, even when controlling for R&D capital.

Another stream of research stresses the importance of R&D in enhancing firms' absorptive capacity of the knowledge generated elsewhere (Cohen and Levinthal 1989, Griffith et al. 2004). This suggests the presence of a complementary relationship between firm's R&D and ICT spillovers, which goes beyond the fact that ICT has originated from research effort (Guellec and van Pottelsberger 2004). The hypothesis that the effect of spillovers depends on facilitating factors in the receiving firms or industries has already been investigated in relation to R&D and human capital spillovers (Griffith et al. 2004, Vandenbussche et al. 2006).<sup>5</sup> The evidence on ICT spillovers, however, is still in its infancy and only a handful of studies present some preliminary results, which do not completely clarify the nature of the relationship between the two assets. For example, Hall at al. (2011) find that, although both R&D and ICT contribute to innovation and productivity, they do not complement each other. Using Dutch companies' data, Polder et al. (2010) observe that ICT is unrelated to R&D activities, but significantly influences the organizational innovation of the companies. On the other hand, Greenan et al. (2001) and Matteucci and Sterlacchini (2004) provide evidence of complementarity between computing equipment and research input in French and Italian firms respectively, particularly when considering the cross-sectional dimension of their data<sup>6</sup>. If such complementarity exists but it is not accounted for, there can be a mis-specification problem in existing empirical studies, which can produce a biased ICT spillover coefficient.

### 3. Methodology and data

## 3.1. Modelling the impact of ICT spillovers on productivity

Our analysis starts from a traditional approach which consists of modelling the output of a single firm as a function of its own inputs and an index of aggregate activity (Helpman 1984, Caballero and Lyons 1989, 1990, Vecchi 2000). Similarly to Jones (1968), we assume that spillovers or external economies are related to the scale of the industry ICT input and are external to the decisions taken by any firm so as to retain the perfectly competitive nature of the model. We will evaluate whether companies' productivity performance is affected by the total stock of ICT capital within each industry, and whether this process is facilitated by firm (R&D) knowledge base. In doing so, we control for several dimensions of heterogeneity (high and low

<sup>&</sup>lt;sup>5</sup> There is an extensive literature investigating the role of absorptive capacity in knowledge or technology transfers. See also Cohen and Levinthal (1989), Coe and Helpman (1995) and Yasar (2012).

<sup>&</sup>lt;sup>6</sup> Brynjolfsson et al. (2002) and Bertschek and Kaiser (2004) provide further evidence on the complementarity between ICT and R&D.

R&D-intensive companies), look at alternative sources of TFP spillovers and assess the presence of various forms of mis-specification.

The starting point of our analysis is a Cobb-Douglas production function<sup>7</sup>, where output  $(Y_{ijt})$  is expressed as a function of capital  $(K_{ijt})$ , labour  $(L_{ijt})$  and R&D capital  $(R_{ijt})$ :

$$Y_{ijt} = A(ICT_{jt})K^{\alpha}_{ijt}L^{\beta}_{ijt}R^{\gamma}_{iit}$$
(1)

where *i* denotes firm, *j* industry and *t* time. The term *A* is the firm total factor productivity and it is here determined by an industry measure of ICT capital  $(ICT_{it})$ . This term will capture the spillovers generated by the diffusion of ICT at the industry level. Since research expenses cannot be separated from capital and labour outlays, R&D capital is assumed to affect firm output via productivity spillovers. Double counting of research implies that firm output elasticity to own R&D capital is significant only if this factor gain excess returns, i.e. it is source of internal knowledge spillovers (Schankerman1981, Guellec and van Pottelsberghe 2004). Also, own knowledge endowment allows a firm to enjoy ICT-related spillovers; these are assumed to be proportional to ICT capital at industry level (van Leeuwen and van der Wiel, 2003). Due to data constraints, we are not able to distinguish between ICT and non-ICT capital at the company level, and therefore we cannot separately identifying industry-wide spillovers from productivity effect of own digital capital. However, as our measure of company capital embeds ICT assets, the estimation of the spillover effect will not be affected by an omitted variable problem. Furthermore, to control for industry size, we normalize ICT endowment with industry employment. Denoting the log of variables in lower case letters, our empirical specification can be written as (benchmark model):

$$y_{ijt} = a_i + a_t + \alpha k_{ijt} + \beta l_{ijt} + \gamma r_{ijt} + \chi i c t_{jt} + \varepsilon_{it}$$
(2)

where  $a_i$  is a company specific intercept (fixed effect),  $a_t$  are time dummies. The coefficients  $\alpha$  and  $\beta$  are standard output elasticities to factor inputs,  $\gamma$  identifies productivity externalities related to firm R&D capital (excess returns),  $\chi$  captures externalities directly associated with the diffusion of GPT at industry level (measured by ICT capital stock per worker).

We then expand equation (2) to include the interaction between company's R&D and industry ICT, in order to account for companies' absorptive capacity:

$$y_{ijt} = a_i + a_t + \alpha k_{ijt} + \beta l_{ijt} + \gamma r_{ijt} + \chi ict_{jt} + \eta r_{ijt} * ict_{ijt} + \varepsilon_{it}$$
(3)

<sup>&</sup>lt;sup>7</sup> The use of other function forms, such as the CES or the translog function, has sometimes been suggested. However, these alternative formulations do not seem to provide substantial improvements to the estimates (Griliches and Mairesse 1984).

where  $\eta$  is the portion of ICT spillovers acquired by the firm through its knowledge base (i.e. its absorptive capacity). The total impact of ICT spillovers is therefore given by  $\chi + \eta r_{ijt}$ , evaluated at different points of the R&D distribution. Equation (3) models the possibility that firms may benefit from ICT spillovers by means of their absorptive capacity ( $\eta > 0$ ,  $\chi=0$ ), or directly without any R&D investments ( $\eta=0$ ,  $\chi>0$ ), or more widely through both channels ( $\eta>0$ ,  $\chi>0$ ). There is reason to believe that only the mostly innovative firms were able to accommodate, and therefore benefit from, the diffusion of ICT in the 1990s. The uptake of the new technology provided firms with new ways of performing tasks, opportunities for developing new lines of business and, above all, alternative forms of information management and business-to-business communications. However, firms were forced to long periods of business re-organization, characterised by experimentation, trials (and failures), and learning. Therefore, firms with a well-established knowledge base, and endowed with highly skilled workforce, are likely to have better exploited efficiency gains associated with ICT at the initial stage of the digital revolution.

Measuring spillovers by introducing an index of aggregate activity is a method that has been largely used in the existing literature (Bernstein and Nadiri, 1989, Caballero and Lyons 1989, 1990, Vecchi 2000). Both aggregate output and aggregate input have acted as proxies for spillovers (Oulton 1996). One drawback of this methodology is that the aggregate variable is likely to pick up unmeasured input variation over the cycle. Also, since the externality index is the same for several companies in a given year, it may be functioning simply as a proxy for a set of time period dummies. The latter in turn could be interpreted in a large number of different ways, without necessarily any role for externalities (see Oulton 1996, Pesaran 2006). To address this issue, we introduce time dummies in all estimations ( $a_t$ ). Therefore, any spillover effect will be net of other cyclical and/or exogenous components.

Our analysis will be based on two aggregate measures of ICT. First, we use ICT at the industry level under the assumption that the productivity of a single company is affected by the investment in ICT in its own industry. Emergence of best practices usually leads to imitation, and hence triggers diffusion of new technologies, especially among competing firms.<sup>8</sup> Moreover, companies may experience productivity gains from innovative practices implemented by their suppliers and customers. Therefore, aggregate ICT at the industry level can only account for spillovers within the industry (horizontal spillovers) but cannot say anything about the presence of spillover across different industries (vertical spillovers). To trace

<sup>&</sup>lt;sup>8</sup> For example, it is not unreasonable to think that the output of a pharmaceutical company is affected by the ICT undertaken in the whole chemical industry.

inter-industry flows of spillovers we use industry series on ICT capital weighted by input-output intermediate transactions' coefficients, as detailed in the following section.

## 3.2 Data sources and methods

We use US company accounts from Compustat database for the time period 1991-2001. The primary data series extracted were net sales, employment, net physical capital, defined as equipment and structures (PPE), and R&D expenditures. Net physical capital at historic cost was converted into capital at replacement costs (Arellano and Bond 1991). Our attention to R&D expenditure is justified by the existing evidence that ICT and R&D may be complementary or independent source of spillovers and they should therefore be analysed within the same framework (Venturini 2011). R&D expenditure was converted into a stock measure using a perpetual inventory method, together with the assumption of a pre-sample growth rate of 5% and a depreciation rate of 15% (see Hall 1990 for details).<sup>9</sup> The Compustat database classifies companies to industries according to the 1987 US Standard Industrial Classification (SIC). This classification was then converted into ISIC Rev. 3 base, which is the one followed by industry-level variables. We merged company- and industry-level sources, obtaining a consistent data set for seventeen industries (twelve manufacturing plus five service industries).

Industry accounts data (ICT, employees, etc.) come from EU KLEMS 2011, R&D expenditure from OECD ANBERD 2009. Such data are used to assess the intra- and interindustry spillovers. Inter-sectoral measures of ICT or R&D spillovers are constructed considering input-output intermediate transactions' coefficients, taken from OECD I-O output table:<sup>10</sup>

$$wICTL_{jt} = \sum_{j=1}^{17} w_{jft} \times ICTL_{ft} = \sum_{j=1}^{17} \frac{M_{jft}}{Y_{jft}} \times ICTL_{ft}$$
$$wRDL_{jt} = \sum_{j=1}^{17} w_{jft} \times RDL_{ft} = \sum_{j=1}^{17} \frac{M_{jft}}{Y_{jft}} \times RDL_{ft}$$

with  $f \neq j$  and t=1991, ..., 2001.  $ICTL_j$  and  $RDL_j$  are respectively ICT capital and R&D capital stock, expressed per unit of workers, of the industry *j* where company *i* is located.  $ICTL_f$  and

<sup>&</sup>lt;sup>9</sup> Companies that did not disclose any data for net sales, employment or net physical capital were excluded from the estimation, as were those companies displaying negative values. We also excluded companies for which the growth rate of these variables was more than 150% or lower than -150. The number of these companies was not very high but their inclusion did affect the computation of labour productivity growth rates and our coefficient estimates. This criterion to remove outliers has been used recently in Aghion et al. (2005) and Bloom and Van Reenen (2002).

<sup>&</sup>lt;sup>10</sup> Input-Output values are available at benchmark years (1990, 1995, 2000 and 2005); intermediate values among such years have been interpolated.

 $RDL_f$  are the value of the surrounding sectors  $(f \neq j)$ .<sup>11</sup>  $w_{jft}$  is the inter-industry coefficient of intermediate transactions between sector j and sector f, defined as ratio between the flow of intermediate inputs sold by sector f to sector j and the gross output of the selling sector, respectively denoted by  $M_{jft}$  and  $Y_{jft}$ .

### 3.2 Summary statistics

Table 1 presents descriptive statistics for the variables used in the regression analysis. We work with an unbalanced panel of 968 firms.

Table 1. Descriptive statistics (1991-2001)									
	Obs	Mean	SD	Min	Max				
ny characteristics									
Output	9,435	2,395	9,549	0.026	181,078				
Employees (thousands)	9,065	11	36	0.004	756				
Physical capital	9,465	780	3,485	0.007	81,143				
R&D capital	9,480	544	2,445	1.008	44,971				
v characteristics									
Intra-industry ICT capital (p.w.)	9,480	5.1	3.7	0.1	36.4				
t Inter-industry ICT capital (p.w.)	9,480	4,247	3,623	494	18,174				
Intra-industry R&D capital (p.w.)	8,022	69,677	37,333	5.9	112,536				
Inter-industry R&D capital (p.w.)	9,480	12,323	13,920	1,273	52,897				
	ny characteristics Output Employees (thousands) Physical capital R&D capital y characteristics Intra-industry ICT capital (p.w.) Inter-industry R&D capital (p.w.)	ObsObsOutput9,435Employees (thousands)9,065Physical capital9,465R&D capital9,465w characteristics9,480Intra-industry ICT capital (p.w.)9,480Inter-industry ICT capital (p.w.)9,480Intra-industry R&D capital (p.w.)8,022	ObsMeanny characteristicsOutput9,435Employees (thousands)9,065Physical capital9,465R&D capital9,480staracteristicsIntra-industry ICT capital (p.w.)9,480f. Inter-industry ICT capital (p.w.)9,480f. Inter-industry R&D capital (p.w.)9,480staractery R&D capital (p.w.)9,480	Obs         Mean         SD <i>ny characteristics</i> 9,435         2,395         9,549           Employees (thousands)         9,065         11         36           Physical capital         9,465         780         3,485           R&D capital         9,480         544         2,445 <i>w characteristics</i> 1         3.7           Intra-industry ICT capital (p.w.)         9,480         5.1         3.7           Inter-industry ICT capital (p.w.)         9,480         4,247         3,623           Intra-industry R&D capital (p.w.)         8,022         69,677         37,333	ny characteristics         Output       9,435       2,395       9,549       0.026         Employees (thousands)       9,065       11       36       0.004         Physical capital       9,465       780       3,485       0.007         R&D capital       9,480       544       2,445       1.008         v characteristics       Intra-industry ICT capital (p.w.)       9,480       5.1       3.7       0.1         a Inter-industry ICT capital (p.w.)       9,480       4,247       3,623       494         Intra-industry R&D capital (p.w.)       8,022       69,677       37,333       5.9				

 $WRDL_{jt}$  Inter-industry R&D capital (p.w.) 9,480 12,525 13,920 1,273 52,897

Notes: Employees are measured in thousands. All other variables are expressed in millions of 1995 dollars. Industry values are expressed per unit of workers (p.w.).

Over the 1991-2001 period, net sales amounted to 2,395 million dollars (at 1995 prices), physical capital stock to 780 millions, while the cumulative value of R&D to 540 millions. On average, US firms employed 11 thousands workers. Moving to industry-level variables, we observe that the stock of ICT per worker, *ICTL*, was relatively small with respect to R&D (5.1 against 69,677 million dollars). More interestingly, whereas own-industry ICT capital is smaller than the inter-industry value (*ICTL* vs *wICTL*), the cumulative value of intra-industry R&D sizeably exceeds inter-industry knowledge capital (*RDL* vs *wRDL*). It witnesses that R&D investment is largely concentrated across sectors, or equivalently that ICT was adopted more pervasively since the outset of the digital revolution. It is therefore reasonable to expect heterogeneous effects on firm productivity from these two types of technologically advanced capital.

Table 2. Average company R&D	) and sp	illover	proxies by	industry (	(1991-2	001)
	Obs	$R_{ijk}$	$ICTL_{jk}$	wICTL <sub>jk</sub>	$RDL_{jk}$	wRDL <sub>jk</sub>

<sup>&</sup>lt;sup>11</sup> Industry values for ICT capital is taken from the EU KLEMS data on the confidential permission of Mary O'Mahony. R&D capital at industry level is computed in a consistent way with company-level R&D stock.

Food & Beverage	160	335	2.0	4,722	4,843	8,042
Textile, Clothing & Footwear	107	64	0.6	7,709	1,506	45,370
Wood	32	175	0.7	1,687	254	5,802
Pulp, Paper & Publishing	216	457	2.6	2,289	4,261	6,277
Chemicals	1,374	836	9.0	2,364	92,345	2,912
Rubber & Plastics	33	775	1.0	3,115	8,752	24,253
Non-metallic minerals	44	68	2.2	1,334	6,777	4,961
Basic metals, etc.	129	52	1.6	1,290	4,944	4,956
·	741	192	3.9	5,025	17,357	21,672
2	3,676	382	5.5	4,523	89,492	8,542
	903	1,363	3.3	9,411	92,497	48,952
	382	133	1.2	4,585	8,504	17,502
Wholesale, Retail	124	84	1.4	4,325	1,625	7,143
Hotels, Restaurant	7	104	0.2	7,988	308	7,071
Communications	43	4,387	23.6	1,649	2,672	4,232
Financial services	51	46	11.5	3,838	1,071	2,045
Business services	1,458	532	4.5	2,126	NA	2,683
TOTAL ECONOMY*	9480	543.7	5.1	4,247	69,677	12,323
	Textile, Clothing & Footwear Wood Pulp, Paper & Publishing Chemicals Rubber &Plastics Non-metallic minerals Basic metals, etc. Machinery Electrical equipment Transport equipment Manufacturing, nec Wholesale, Retail Hotels, Restaurant Communications Financial services Business services	Textile, Clothing & Footwear107Wood32Pulp, Paper & Publishing216Chemicals1,374Rubber & Plastics33Non-metallic minerals44Basic metals, etc.129Machinery741Electrical equipment3,676Transport equipment903Manufacturing, nec382Wholesale, Retail124Hotels, Restaurant7Communications51Business services1,458	Tool & Beverage10764Textile, Clothing & Footwear10764Wood32175Pulp, Paper & Publishing216457Chemicals1,374836Rubber & Plastics33775Non-metallic minerals4468Basic metals, etc.12952Machinery741192Electrical equipment3,676382Transport equipment9031,363Manufacturing, nec382133Wholesale, Retail12484Hotels, Restaurant7104Communications5146Business services1,458532	Tool & Boverage107640.6Textile, Clothing & Footwear107640.6Wood321750.7Pulp, Paper & Publishing2164572.6Chemicals1,3748369.0Rubber & Plastics337751.0Non-metallic minerals44682.2Basic metals, etc.129521.6Machinery7411923.9Electrical equipment3,6763825.5Transport equipment9031,3633.3Manufacturing, nec3821331.2Wholesale, Retail124841.4Hotels, Restaurant71040.2Communications514611.5Business services1,4585324.5	Tool & Beverage107640.67,709Wood321750.71,687Pulp, Paper & Publishing2164572.62,289Chemicals1,3748369.02,364Rubber & Plastics337751.03,115Non-metallic minerals44682.21,334Basic metals, etc.129521.61,290Machinery7411923.95,025Electrical equipment3,6763825.54,523Transport equipment9031,3633.39,411Manufacturing, nec3821331.24,585Wholesale, Retail124841.44,325Hotels, Restaurant71040.27,988Communications434,38723.61,649Financial services514611.53,838Business services1,4585324.52,126	Tool & Develage107640.67,7091,506Wood321750.71,687254Pulp, Paper & Publishing2164572.62,2894,261Chemicals1,3748369.02,36492,345Rubber & Plastics337751.03,1158,752Non-metallic minerals44682.21,3346,777Basic metals, etc.129521.61,2904,944Machinery7411923.95,02517,357Electrical equipment3,6763825.54,52389,492Transport equipment9031,3633.39,41192,497Manufacturing, nec3821331.24,5858,504Wholesale, Retail124841.44,3251,625Hotels, Restaurant71040.27,988308Communications434,38723.61,6492,672Financial services514611.53,8381,071Business services1,4585324.52,126NA

Notes: \*excludes real estate activities.

Table 2 displays industry distribution of firm R&D capital and industry-level variables. In the manufacturing sector, for both kinds of R&D indicators, transport equipment has the highest level of R&D (1,363 and 92,497 million dollars, respectively), followed by chemicals and electrical equipment. However, these two sectors remarkably differ as the degree of R&D engagement is less concentrated in the latter, as shown by company's R&D stock (382 vs 836 million dollars). Chemicals also reveal the highest value of own-industry ICT capital (per worker). Instead, transport equipment stands out for both types of inter-industry spillovers (*wICTL* and *wRDL*). In the tertiary sector, communication services are characterised by the highest values of company R&D capital, industry-level stocks of ICT and R&D.

#### 4. Results

## 4.1 Benchmark specification

We start our empirical analysis with the estimation of a log linear production function where output is explained by labour, physical capital and R&D capital. We then expand our specification to include our spillover proxies. All estimates are carried out using panel data methods (Fixed Effect estimator) to account for cross sectional heterogeneity. Time dummies are included in all specifications. In all tables we control for the presence of endogeneity by showing results based on a Generalised Method of Moments (GMM) estimator, with lagged values of company variables used as instruments (Hayashi, 2000; Baum et al., 2003); we limit the numbers of lags to 2 to avoid upward biased coefficients (Roodman 2009). The deterministic elements of the empirical model are trated as exogenous, as well as the industry-level variables. We also correct the covariance matrix for arbitrary heteroskedasticity and for the presence of first order serial correlation. At the bottom of the table we report the Kleibergen and Paap (2006) test of under-identification and the Hansen-J (1982) test of over-identifying restrictions. Both tests show that our models are correctly identified and the instruments satisfy the orthogonality conditions.

Table 3 reports our first set of results. In column (1) our estimates for labour and capital elasticity are consistent with prior knowledge of factor shares. Existing evidence on R&D elasticity provides quite a large range of values, from 0.04 (Griliches 1979, 1984, Bloom et al. 2012) to 0.18 (Griliches and Mairesse 1984), and our point estimate of 0.125 lies within this range. The hypothesis of constant returns to scale (CRS) is never rejected, as show by the CRS test at the bottom of the table. In columns (2-4) we assess the importance of ICT spillovers by including ICT at the industry level, as in equation (2). We consider intra and inter industry spillovers individually (columns 2 and 3) and jointly (Column 4). The two measures produce profoundly different results. Intra industry spillovers have a negative and significant impact on productivity. These results are consistent, for example, with Stiroh (2002) who finds that ICT capital per employee is negatively related to TFP growth in US manufacturing industries. On the other hand, when we consider the inter-industry effect, the coefficient estimate of our weighted spillover variable is positive and statistically significant and it suggests that a 1% increase in ICT investments across all industries increases companies' productivity by approximately 0.21%. This effect is not trivial but it does not offset the negative impact from ICT investments within the company's own industry.

	(1)	(2)	(3)	(4)
Company level variables				
Employment	0.765***	0.783***	0.774***	0.790***
	(0.034)	(0.035)	(0.035)	(0.035)
Physical capital	0.120***	0.109***	0.119***	0.110***
	(0.026)	(0.026)	(0.026)	(0.026)
R&D capital	0.125***	0.135***	0.111***	0.119***
	(0.020)	(0.021)	(0.021)	(0.021)
Intra industry ICT		-0.378***		-0.330***
		(0.040)		(0.039)
Inter industry ICT			0.258***	0.206***
			(0.036)	(0.034)
Obs	6,876	6,745	6,704	6,704
R-squared	0.756	0.758	0.757	0.760
No. of Firms	968	945	938	938
CRS (P value)	0.560	0.122	0.789	0.246
Kleibergen-Paap LM stat P-value	< 0.001	< 0.001	< 0.001	< 0.001
Hansen J test P-value	0.135	0.308	0.187	0.322

All equations are estimated using a Fixed effects (FE) estimator. Time dummies are included in all specifications. Standard errors robust to heteroskedasticity and first-order serial correlation reported in parentheses. The dependent variable is log output (total sales). CRS is the a test for the null hypothesis of constant returns to scale. All company level variables have been instrumented with their own values at time t-1 and t-2. In the presence of heteroscedasticity, the Hansen J statistic is an appropriate test of the null hypothesis of instrument validity. The Kleibergen-Paap LM statistic tests the null hypothesis that the matrix of reduced-form coefficients in the first-stage regression is under-identified. \*\*\*, \*\*, \*\* significant at 1, 5 and 10%.

The two industry variables appear to pick up different types of technological externalities which affect productivity in the opposite direction. A negative productivity effect from aggregate within industry ICT may be due to two possible causes. Firstly, the new technology requires a re-organisation of the production process which implies large adjustment costs for companies, particularly in the initial stage of diffusion (Bresnahan 2003, Kiley, 2001). Secondly, it is possible that the negative sign of own-industry ICT investment is due to a business stealing effect, whereby companies that find new and more efficient applications of ICT will negatively affect the productivity of their competitors (Bloom et al. 2012)<sup>12</sup>. We will further elaborate these two explanations later in the work.<sup>13</sup> The positive effect of inter-industry ICT capital is consistent with previous evidence on the ability of information technology to enable of productivity spillovers across sectors. Wolff (2011) shows that, as long as information technology to may enable of TFP growth. Bernstein (2000) studies the role of

<sup>&</sup>lt;sup>12</sup> The business stealing effect (or product market rivalry) is estimated in Bloom et al. (2012) in relation to R&D spillovers and for a similar sample of companies to the one used in this study.

<sup>&</sup>lt;sup>13</sup> A typical concern working with microeconomic data in absence of company-level deflators is that the use of industry price index may be source of severe measurement errors that bias estimates. As suggested by Bloom et al. (2012, p. 20), one can check robustness of results by including the contemporaneous and the lagged values of industry output. When do this, estimates do change only marginally. Results available on request.

communication infrastructure as a conduit of R&D spillovers from the United Sates to the Canadian manufacturing sector.<sup>14</sup> In the reminder of the paper we are going to further investigate these results addressing three possible types of mis-specification which could affect the estimation of our benchmark model: the existence of complementarities between companies' R&D and ICT spillovers, the impact of R&D spillovers and cyclicality and the timing of the dynamic specification of the ICT spillover effect.

#### 5. Extensions

## 5.1. ICT spillovers and absorptive capacity

In this section we extend our model to account for the role of absorptive capacity, i.e. the firm's ability to use the technology developed elsewhere. Our main hypothesis is that such absorptive capacity is a function of the firm's own investment in R&D, i.e. more innovative firms are better equipped with the necessary skills and resources to take advantage of the new technology. This phenomenon is captured by the instruction of an interaction between companies' R&D and the two spillover proxies, as described in Equation (3). A positive and significant coefficient on the interaction term would provide evidence of productivity spillovers from ICT capital via the firm's absorptive capacity, revealing a complementarity between the technology endowment of the company and that of the environment to which it operates.

Table 4 presents the results of the estimation of equation 3. Our estimates of the interaction term are positive and significant both when considering intra and inter industry spillovers, hence confirming the mutually self-enforcing effect of firm's innovative effort and industry ICT capital (Columns 1-3). Only when we include both spillovers and interaction terms in the same specification (column 3) the interaction between own R&D and inter-industry ICT becomes insignificant, possibly due to problems of collinearity (the correlation coefficient between the two interaction terms is 0.71). The interaction effect between company own R&D and inter industry ICT also has some perverse effects on the company R&D capital elasticity, which ranges from 0.043 (non statistically significant, see col. 2) to 0.299 (statistically significant, see col. 3). For this reason, in the reminder of our analysis we will only include the interaction between own-company R&D and intra-industry ICT spillovers, i.e. we will carry on with the specification presented in column 4.

<sup>&</sup>lt;sup>14</sup> Lee (2005) and Zhu and Jeon (2007) document that advanced telecom infrastructures have also enabled relevant technology transfers across countries.

Table 4. ICT spillover and absorptive capacity									
	(1)	(2)	(3)	(4)					
Company level variables									
Employment	0.781***	0.772***	0.790***	0.788***					
	(0.035)	(0.035)	(0.035)	(0.035)					
Physical capital	0.112***	0.123***	0.112***	0.114***					
	(0.026)	(0.027)	(0.027)	(0.026)					
R&D capital	0.111***	0.043	0.229**	0.098***					
-	(0.022)	(0.043)	(0.114)	(0.023)					
Industry level variables and interactions									
Intra industry ICT	-0.441***		-0.525***	-0.390***					
	(0.044)		(0.15)	(0.043)					
Firm R&D*intra industry ICT	0.014***		0.039*	0.0129***					
	(0.004)		(0.020)	(0.004)					
Inter industry ICT		0.221***	0.287***	0.202***					
		(0.040)	(0.074)	(0.034)					
Firm R&D*inter industry ICT		0.008**	-0.021						
		(0.004)	(0.017)						
Obs.	6,745	6,704	6,704	6,704					
R-squared	0.759	0.758	0.760	0.761					
No. of Firms	945	938	938	938					
Kleibergen-Paap LM statistic P-value	< 0.001	< 0.001	< 0.001	< 0.001					
Hansen J test P value	0.318	0.191	0.335	0.321					

## Table 4. ICT spillover and absorptive capacity

#### Total spillover effect (estimate from column 4)

Percentile	5%	10%	25%	50%	75%	90%	95%
Ln(R&D)	1.23	1.92	3.00	4.10	5.23	6.64	7.69
a) Intra industry	-0.37	-0.37	-0.35	-0.34	-0.32	-0.30	-0.29
b) Inter industry	0.20	0.20	0.20	0.20	0.20	0.20	0.20
Total	-0.16	-0.14	-0.11	-0.08	-0.05	-0.02	0.01
P-value	[0.00]	[0.00]	[0.00]	[0.01]	[0.02]	[0.05]	[0.09]

All equations are estimated using a Fixed effects (FE) estimator. Time dummies are included in all specifications. Standard errors robust to heteroskedasticity and first-order serial correlation reported in parentheses. The dependent variable is log output (total sales). All company level variables have been instrumented with their own values at time t-1 and t-2. In the presence of heteroscedasticity, the Hansen J statistic is an appropriate test of the null hypothesis of instrument validity. The Kleibergen-Paap LM statistic tests the null hypothesis that the matrix of reduced-form coefficients in the first-stage regression is under-identified. \*\*\*, \*\*, \*\* significant at 1, 5 and 10%. The total intra industry spillover effect is derived by multiplying the interaction coefficient by different values of R&D and subtracting the coefficient on intra-industry ICT.

At the bottom of Table 4 we compute the total spillover effect at different points of the R&D distribution. Despite the positive interaction, the total intra-industry spillover effect remains negative, although decreasing with the size of firm's knowledge base. The total spillover effect from ICT is therefore negative for the majority of the companies. Only those at upper tail of the distribution (over the 95 percentile) were able to significantly benefit from ICT, whose net effect is however economically modest (0.01, p-value: 0.09). In other words, at the outset of the information age, the negative effects of ICT associated with business-stealing or restructuring appear to prevail on TFP-enhancing impact for a typical US company.

With reference to the two possible explanations for the negative impact of ICT, the significant and positive sign of the interaction term seems to corroborate the restructuring rather than the business-stealing hypothesis, given that the negative effect of ICT within the industry is confined to less R&D-intensive companies only. If we had found no evidence of complementary between company's absorptive capacity and own-industry ICT, we could have inferred that ICT adoption only increases productivity of adopting companies. By contrast, our results suggest that own-industry ICT may be a source of externalities to the extent to which firms accommodate their arrival investing in R&D, or such technologies spread out throughout the economy. The latter aspect will be considered in the assessment of delayed effects of ICT (section 5.3). It should also be observed that our findings identify another role for R&D-based knowledge with respect to the existing literature, i.e. firm's absorptive capacity is pre-requisite not only to imitate innovation (Griffith et al. 2004), but also to drain potential productivity gains associated with other companies' investment on technologically advanced (physical) assets. This is another novel piece of evidence of our work.

## 5.2. Robustness checks

In this section we further extend specification 3 to account for other factors that are related to productivity enhancement and whose absence could bias the coefficient estimates of the spillover variables. As discussed in Acharya and Basu (2010) among others, R&D is a factor that can generate productivity spillovers and, if not included in our specification, its effect could be erroneously captured by the ICT spillover variable. Similarly to ICT capital, we construct an intra and an inter industry R&D term following the methodology discussed in section 3.2. Results are presented in Table 5, columns (1-4).

	(1)	(2)	(3)	(4)
Company level variables				
Employment	0.793***	0.788***	0.793***	0.789***
	(0.039)	(0.035)	(0.039)	(0.039)
Physical capital	0.114***	0.114***	0.115***	0.115***
	(0.030)	(0.026)	(0.030)	(0.030)
R&D capital	0.092***	0.095***	0.090***	0.093***
1	(0.025)	(0.023)	(0.025)	(0.025)
Industry level variables and interactions	× /	· · · ·	× ,	× ,
Intra industry ICT	-0.494***	-0.329***	-0.371***	-0.410***
5	(0.057)	(0.048)	(0.065)	(0.060)
Firm R&D*intra industry ICT	0.014***	0.014***	0.016***	0.015***
5	(0.005)	(0.004)	(0.005)	(0.005)
Inter industry ICT	0.207***	0.458***	0.448***	0.198***
5	(0.034)	(0.084)	(0.092)	(0.038)
Intra industry R&D	0.046**	· · · ·	0.029	0.043**
5	(0.019)		(0.019)	(0.018)
Inter industry R&D	× ,	-0.302***	-0.289***	× ,
5		(0.084)	(0.091)	
Hours worked		· · · ·		0.385***
				(0.141)
				. ,
Obs.	5814	6,704	5814	5814
R-squared	0.743	0.762	0.744	0.744
No. of Firms	785	938	785	785
Kleibergen-Paap LM statistic P-value	< 0.001	< 0.001	< 0.001	< 0.001
Hansen J test P-value	0.451	0.327	0.474	0.471

## Table 5. Controlling for R&D spillovers and cyclical labour utilization

### Total spillover effect for R&D-intensive firms (estimate from column 4)

<b>Percentile</b> Ln(R&D)	<b>5%</b> 1.23	<b>10%</b> 1.92	<b>25%</b> 3.00	<b>50%</b> 4.10	<b>75%</b> 5.23	<b>90%</b> 6.64	<b>95%</b> 7.69
a) Intra industry	-0.39	-0.38	-0.37	-0.35	-0.33	-0.31	-0.29
b) Inter industry	0.20	0.20	0.20	0.20	0.20	0.20	0.20
Total	-0.18	-0.15	-0.12	-0.09	-0.06	-0.01	0.02
P-value	[0.00]	[0.00]	[0.01]	[0.01]	[0.03]	[0.07]	[0.13]

All equations are estimated using a Fixed effects (FE) estimator. Time dummies are included in all specifications. Standard errors robust to heteroskedasticity and first-order serial correlation reported in parentheses. The dependent variable is log output (total sales). All company level variables have been instrumented with their own values at time t-1 and t-2. In the presence of heteroscedasticity, the Hansen J statistic is an appropriate test of the null hypothesis of instrument validity. The Kleibergen-Paap LM statistic tests the null hypothesis that the matrix of reduced-form coefficients in the first-stage regression is under-identified. \*\*\*, \*\*, \* significant at 1, 5 and 10%. The total intra industry spillover effect is derived by multiplying the interaction coefficient by different values of R&D and subtracting the coefficient on intra-industry ICT.

The intra-industry R&D spillover is positive and significant but only when we exclude inter-industry R&D effects. The latter are significant but have a negative sign, suggesting that the aggregate R&D outside the company's own industry reduces the company's productivity. It is interesting, however, that the inclusion of the R&D spillover terms do have only a moderate effect on the size of the ICT spillovers. The last column of Table 5 introduces the industry total hours worked, to capture the impact of cyclical labour utilization on productivity. Existing empirical evidence shows that variations in labour effort over the cycle can be mistaken for

spillover effects (Hall 1998, Vecchi 2000) and it is therefore important to account for this additional source or productivity. More recently Oliner et al. (2008) suggested that the resurgence in labour productivity in the 1990s could be caused by normal cyclical dynamics. The coefficient on the total number of hours worked is indeed positive and statistically significant but its introduction does not change our conclusions in relation to the ICT spillover effects. Using this last set of coefficient estimates we compute again the total ICT spillover effect, evaluated at different point of the distribution of companies' R&D capital stock. We report these computations at the bottom of Table 5. The total ICT spillover effect is still negative, with the only exception of the firms with a very large knowledge base (i.e. those above the threshold of 90 percentile of R&D distribution).

We further investigate this result by presenting, in Table 6, the estimation of equation 3 for two groups of industries, high tech and low tech.<sup>15</sup> Column (1) presents the results for the overall sample for comparison purposes. For the R&D-intensive companies we still find a negative intra-industry ICT spillover effect and a positive inter-industry spillover. The magnitude of the latter effect is higher than for the overall sample. For the non-R&D intensive sectors we do not find any positive spillovers. However, two points are worth noticing about this last set of results. Firstly, the majority of companies are included in the high-tech sector. This is a natural outcome as R&D is concentrated in this sector. Secondly, for the low-tech companies, the coefficient on physical capital is not statistically significant. Further investigation reveals that, once we dropped all the industry variables that are not statistically significant, the physical capital coefficient becomes positive and significant and of similar magnitude as in the rest of our results (Column 4).

For those companies included in the R&D-intensive sectors we find a larger interindustry spillover effect. This, together with the lower intra-industry ICT spillover, produces a total spillover effect whose net value is close to zero for this kind of companies (see the bottom section of Table 6). It suggests that the most innovative firms, competing in technologically advanced markets, were able to fully offset the negative intra-industry spillover of ICT with their own absorptive capacity and intra-industry spillover effects. This result strengthens the complementary relationship between innovative behaviour and ICT spillovers.

<sup>&</sup>lt;sup>15</sup> High-tech or R&D-intensive companies belong to the following industries: Chemicals (cat. 24, ISIC Rev. 3), Electrical equipment (30t33), Transport equipment (34t35), Communications (64). Low-tech companies' group comprises all firms classified in the remaining industries.

Table 6: R&D versus non-R&D intensive sectors									
	(1)	(2)	(3)	(4)					
	All	R&D	Non R&D	Non R&D					
		intensive	intensive	intensive					
Company level variables									
Employment	0.793***	0.780***	0.825***	0.814***					
	(0.039)	(0.045)	(0.070)	(0.050)					
Physical capital	0.114***	0.122***	0.082	0.099***					
	(0.030)	(0.033)	(0.052)	(0.038)					
R&D capital	0.092***	0.096***	0.042	0.075***					
	(0.025)	(0.030)	(0.031)	(0.027)					
Industry level variables and interactions									
Intra industry ICT	-0.494***	-0.349**	-0.198**	-0.226***					
	(0.057)	(0.151)	(0.082)	(0.043)					
Firm R&D*intra industry ICT	0.014***	0.013**	-0.008						
	(0.005)	(0.006)	(0.008)						
Inter-industry ICT	0.207***	0.313***	-0.058						
	(0.034)	(0.067)	(0.089)						
Intra-industry R&D	0.046**	-0.045	0.008						
	(0.019)	(0.116)	(0.020)						
Obs.	5814	4,336	1,478	2409					
R-squared	0.743	0.747	0.762	0.815					
No. of Firms	785	588	197	357					
Kleibergen-Paap LM statistic P-value	< 0.001	< 0.001	< 0.001	< 0.001					
Hansen J test P-value	0.451	0.643	0.184	0.462					

## Table 6: R&D versus non-R&D intensive sectors

#### Total spillover effect (estimate from column 2)

Percentile	5%	10%	25%	50%	75%	90%	95%
Ln(R&D)	1.33	1.97	3.07	4.23	5.41	6.89	8.06
a) Intra industry	-0.33	-0.32	-0.31	-0.29	-0.27	-0.25	-0.24
b) Inter industry	0.21	0.21	0.21	0.21	0.21	0.21	0.21
Total	-0.10	-0.09	-0.06	-0.02	0.01	0.05	0.08
P-value	[0.90]	[0.94]	[0.98]	[0.90]	[0.82]	[0.72]	[0.64]

All equations are estimated using a Fixed effects (FE) estimator. Time dummies are included in all specifications. Standard errors robust to heteroskedasticity and first-order serial correlation reported in parentheses. The dependent variable is log output (total sales). All company level variables have been instrumented with their own values at time t-1 and t-2. In the presence of heteroscedasticity, the Hansen J statistic is an appropriate test of the null hypothesis of instrument validity. The Kleibergen-Paap LM statistic tests the null hypothesis that the matrix of reduced-form coefficients in the first-stage regression is under-identified. \*\*\*, \*\*, \*\* significant at 1, 5 and 10%. The total intra industry spillover effect is derived by multiplying the interaction coefficient by different values of R&D and subtracting the coefficient on intra-industry ICT.

# 5.3 The lagged effect of ICT spillovers

In the earlier sections of our work we have shown that, at the uptake of the new technological age, US companies did not gain productivity benefits from ICT adoption within the industry where they operated, and that two competing explanations may be behind such an effect (restructuring vs business-stealing). The finding that only the most innovative firms were able to gain some advantage from industry ICT corroborates the hypothesis that the negative spillover may have been induced by restructuring imposed by the early diffusion of the new digital technologies. Indeed, the main benefits of ICT are related to their networking abilities (information management, data exchange, firm connectivity, etc), and firms need to re-organize their business to fully benefit from technological advancements of contiguous companies.

As a further test of the restructuring hypothesis we now control for a lagged impact of ICT spillovers on productivity. As discussed in Aghion (2002) among others, the adoption of ICT imposes long periods of experimentation and a firm or sector typically learns the new technology from the experience of others. To test for the 'lagged ICT spillover hypothesis' we re-estimate equation (3) using lagged values of all the ICT spillover proxies. Table 7 reports results obtained for the overall sample of companies. Col. (1) displays our key findings of Table 5; in the subsequent sections we report estimates obtained considering different lags for the explanatory variables (1, 3 and 5 years). For each group of estimates, we run the empirical model by first lagging only the intra-industry ICT variable (*ICTL*); then, we lag all industry-level variables. This will help to properly account for the different dynamics in the productivity impact of the various sources of productivity spillover.

Results in table 7 change substantially when we consider different lags of the spillover variables. At time t-1 we still have a negative intra industry ICT spillover and a positive interindustry effect. The former becomes positive but not statistically significant at time (t-3). However, when we consider a 5-lag specification both intra and inter industry effects of information technology are positive and significant. It is interesting to note that, over time, the importance of the complementarity between company R&D and industry ICT decreases and it eventually becomes statistically insignificant. Hence, while in the short run firms' absorptive capacity is necessary to reap the benefits of the new technology, over time the technology becomes more established and the benefits from technological spillovers are more widespread.

Table 7: Delayed effects of ICT											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)				
		1-year	1-y lags	3-year	3-y lags	5-year	5-y lags				
		lags	all ind.	lags	all ind.	lags	all ind.				
		ICTL	variables	ICTL	variables	ICTL	variables				
Company level variables											
Employment	0.793***	0.788***	0.789***	0.812***	0.796***	0.900***	0.840***				
	(0.039)	(0.039)	(0.039)	(0.046)	(0.048)	(0.070)	(0.079)				
Physical capital	0.114***	0.114***	0.117***	0.091***	0.102***	0.024	0.044				
	(0.030)	(0.0297)	(0.030)	(0.033)	(0.035)	(0.048)	(0.055)				
R&D capital	0.092***	0.095***	0.092***	0.104***	0.120***	0.116***	0.132***				
	(0.025)	(0.025)	(0.025)	(0.027)	(0.026)	(0.038)	(0.036)				
Industry level variables and interactions		× /	~ /			× ,					
Intra industry ICT	-0.494***	-0.338***	-0.374***	0.041	0.039	0.146*	0.330***				
	(0.057)	(0.057)	(0.058)	(0.063)	(0.069)	(0.084)	(0.104)				
Firm R&D*intra-industry ICT	0.014***	0.015***	0.018***	0.0043	0.014**	-0.013	-0.007				
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.008)	(0.009)				
Inter-industry ICT	0.207***	0.177***	0.169***	0.192***	0.159***	0.190***	0.145***				
,	(0.034)	(0.037)	(0.036)	(0.040)	(0.043)	(0.045)	(0.049)				
Intra-industry R&D	0.046**	0.034*	0.034*	0.010	-0.005	0.033	-0.023				
-	(0.019)	(0.018)	(0.018)	(0.019)	(0.020)	(0.028)	(0.0329)				
Obs.	5814	5,814	5,814	5,256	5,128	4,071	3,616				
R-squared	0.743	0.743	0.743	0.709	0.770	0.764	0.708				
No. of Firms	785	785	785	779	770	764	708				
Kleibergen-Paap LM statistic P-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001				
Hansen J test P-value	0.451	0.462	0.427	0.627	0.446	0.683	0.857				

All equations are estimated using a Fixed effects (FE) estimator. Time dummies are included in all specifications. Standard errors robust to heteroskedasticity and first-order serial correlation reported in parentheses. The dependent variable is log output (total sales). All company level variables have been instrumented with their own values at time t-1 and t-2. In the presence of heteroscedasticity, the Hansen J statistic is an appropriate test of the null hypothesis of instrument validity. The Kleibergen-Paap LM statistic tests the null hypothesis that the matrix of reducedform coefficients in the first-stage regression is under-identified. \*\*\*, \*\*, \* significant at 1, 5 and 10%. The total intra industry spillover effect is derived by multiplying the interaction coefficient by different values of R&D and subtracting the coefficient on intra-industry ICT.

### 6. Conclusions

This paper has provided new evidence on the presence of ICT spillovers in the US economy in the 1990s, and on the complementarity between ICT spillovers and companies' innovative effort. We have looked a two different definitions of ICT spillovers with the aim of capturing the complex way in which ICT has affected companies' performance. Our results confirm the presence of important ICT spillover effects, but the direction of these effects differs according to the type of spillover we consider. In fact, while inter-industry spillovers are positive and significant in all specifications, intra industry spillovers have a negative effect on productivity. This suggests that in earlier stages of diffusion, ICT may have favoured connectivity with upstream and downstream sectors, but it did not positively contribute to firm productivity growth within the sector, probably due to competition effects and restructuring. We have also found that R&D and ICT complement each other and that only the most innovative firms were able to capture quite rapidly inter-industry spillovers. These results are robust to the inclusion of alternative sources of spillovers and cyclical variations in the labour effort over the business cycle.

Our analysis also provides further evidence on the lagged impact of a new technology on productivity confirming the GPT prediction that the benefits of a new technology become stronger over time. In fact, when we introduced lagged spillovers in our model, both intra and inter industry spillovers become positive and significant. At the same time, the importance of own companies' R&D investments become less relevant at later stages of diffusion of the technology. This implies that in the long run the effect of the new technology is pervasive. Further research is needed to assess the important of lagged ICT spillovers in different countries, different time periods and alternative measures of the ICT spillover proxies.

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#### REFERENCES

- Acharya, R., Basu, S. 2010. ICT and TFP growth: Intangible capital or productive externalities?, Industry Canada Working Paper 2010-1.
- Aghion, P. 2002. Schumpeterian growth theory and the dynamics of income inequality. Econometrica 70(3), pp. 855-882.
- Aghion, P., Howitt, P., 1998. On the macroeconomic effects of major technological change. In E. Helpman (Ed.), General Purpose Technologies and Economic Growth, MIT Press, Cambridge MA.
- Aghion, P., Bloom, N., Blundell, R., Griffith, R., Howitt, P.,2005. Competition and innovation: An inverted U relationship. Quarterly Journal of Economics, pp. 701-728.
- Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo Evidence and an application to employment equations. Review of Economic Studies 58, pp. 277-297.
- Atrostic, B. K., Nguyen, S., 2005. IT and productivity in US manufacturing: Do computer networks matter? Economic Enquiry 43(3), pp. 493-506.
- Baum, C.F., Schaffer, M.E., Stillman, S. 2003. Instrumental variables and GMM: Estimation and testing, Stata Journal 3(1), pp 1-31.
- Basu, S., Fernald, J.G., Oulton, N., Srinivassan, S., 2003. The case of the missing productivity growth: Or, does information technology explain why productivity accelerated in the United States but not in the United Kingdom? NBER Working paper No. 10010.
- Bernstein, J.I., 2000. Canadian manufacturing, U.S. R&D spillovers, and communication infrastructure. Review of Economics and Statistics 82(4), pp. 608-615.
- Bernstein, J.I., Nadiri, M.I., 1989. Research and Development and Intra-industry Spillovers: An Empirical Application of Dynamic Duality, Review of Economic Studies, 56(2), pp 249-267.
- Bertschek, I., Kaiser, U. 2004. Productivity effects of organizational change: Microeconometric evidence, Management Science 50(3), pp. 394-404.
- Biscourp, P., Crepon, B., Heckel, T., Riedinger, N., 2002. How do firms respond to cheaper computers? Microeconometric evidence for France based on a production function approach?, Economie et Statistique No 355-356.
- Bloom, N., Van Reenen, J., 2002. Patents, real options and firm performance, Economic Journal 112(478), pp. C97-C116.
- Bloom, N., Schankerman, M., Van Reenen, J., 2012. Identifying technology spillovers and product market rivalry, CEP working paper 675/2005, Revision April 2012
- Bresnahan, T.F., 1986. Measuring the Spillovers from technical advance: Mainframe computers in financial services. The American Economic Review 76 (4), pp. 742-755.
- Bresnahan, T.F., Trajtemberg, M., 1995. General Purpose Technologies: 'Engines of growth'? Journal of Econometrics 65, pp. 83-108.

- Bresnahan, T.F., 2003. The Contribution of Information Technology to Economic Growth. In: Jean-Touffut P. (Ed.) Institutions, Innovation and Growth: Selected Economic Papers, Edward Elgar.
- Brown, J. R., Fazzari, S. M. and Peterrns, B. C. (2009), Financing Innovation and Growth: Cash Flow, External Equity, and the 1990s R&D Boom. The Journal of Finance, 64: 151–185.
- Brynjolfsson E., Hitt, L.M., 2000. Beyond computation: Information technology, organisational transformation and business performance. Journal of Economic Perspectives 14 (4), pp. 23-48.
- Brynjolfsson E., Hitt, M., 2003. Computing productivity: Firm-level evidence, The Review of Economics and Statistics, 85(4), pp. 793-808.
- Brynjolfsson, E. Hitt, L., Yang, S. 2002. Intangible assets: How the interaction of computers and organizational structure affects stock market valuations, Brookings Papers on Economic Activity, 33(1), pp. 137-198.
- Caballero R.J., Lyons, R.K., 1989. The role of external economies in U.S. manufacturing. NBER Working Paper No 3033.
- Caballero R.J., Lyons, R.K., 1990. Internal versus external economies in European industry. European Economic Review 34, pp. 805-30.
- Colecchia, A., Schreyer, P., 2001. ICT Investment and economic growth in the 1990s: Is the United States a Unique Case?, OECD, Paris.
- Cohen, W.M., Levinthal, D.A., 1989. Innovation and learning: the two faces of R&D. The Economic Journal 99, pp. 569–596.
- Coe, D.T., Helpman, E., 1995. International R&D spillovers. European Economic Review 39(5), 859-887.
- Criscuolo, C., Waldron, K., 2003. E- commerce and firm productivity. Economic Trends 600, pp. 52-57.
- Draca, M., Sadun, R., Van Reenen, J., 2007. ICT and Productivity. In Mansell, R., Avgerou, C., Quah, D., Silverstone, R. (Eds) Handbook of Information of Information and Communication Technologies, Oxford University Press.
- Griffith, R., Redding, S., Van Reenen, J. 2004. Mapping the two faces of R&D: productivity growth in a panel of OECD industries, The Review of Economics and Statistics 86(4), pp. 883-895.
- Griliches, Z., 1979. Issues in assessing the contribution of research and development to productivity growth. Bell Journal of Economics 10 (1), pp. 92-116.
- Griliches, Z., 1984. R&D, patents, and productivity. Chicago: University of Chicago Press.
- Griliches, Z., 1990. Patent statistics as economic indicators: A survey. Journal of Economic Literature 28 (4), pp 1661-1707.
- Griliches, Z., 1992. The search for R&D spillovers, The Scandinavian Journal of Economics 94, pp. 29-47.

- Griliches, Z., Mairesse, J., 1984. Productivity and R&D at the firm level. In: Griliches, Z. (Ed.) R&D, Patents and Productivity. Chicago: University of Chicago Press.
- Griliches Z., Mairesse, J., 1995. Production functions: The search for identification. NBER Working Paper 5067.
- Guellec, D., van Pottelsberghe, B., 2004. From R&D to productivity growth: Do the institutional settings and the source of funds of R&D matter? Oxford Bulletin of Economics and Statistics 66(3), pp. 353-378.
- Hall, R. E. 1988. The Relation between price and marginal cost in U.S. Industry, Journal of Political Economy, 96(5), pp. 921-947.
- Hall, B.H., 1990. The manufacturing master file 1959-1987. NBER Working Paper No. 3366.
- Hall, B.H., Lotti, F., Mairesse, J., 2011. Evidence on the Impact of R&D and ICT Investment on Innovation and Productivity in Italian Firm mimeo.
- Hansen, L.P., 1982. Large sample properties of Generalized Method of Moments estimators, Econometrica 50(4), pp. 1029-1054.
- Haskel, J., Wallis, G., 2010. Public Support for Innovation, Intangible Investment and Productivity Growth in the UK Market Sector, IZA Discussion Papers 4772, Institute for the Study of Labor (IZA).
- Hayashi, F. 2000. Econometrics. Princeton University Press.
- Helpman, E., 1984. The factor content of foreign trade. The Economic Journal 94, pp. 84-94.
- Hornstien, A., Krusell, P. 1996. Can Technology Improvements Cause Productivity Slowdowns?, in B.S. Bernanke and J. J. Rotemberg, eds., *Macroeconomics Annual 1996*. Cambridge, Mass.: MIT Press, pp. 209–59.
- Hornstein, A., Krusell, P. 2000. The IT revolution: is it evident in the productivity numbers?, Economic Quarterly, Federal Reserve Bank of Richmond, issue Fall, pp 49-78.
- Inklaar, R., Timmer, M., van Ark, B., 2008. Market services productivity Across Europe and the US. Economic Policy 23, 139-194.
- Jones, R., 1968. Variable returns to scale in general equilibrium theory. International Economic Review 9, pp 261-272.
- Jaffe, A. B. 1986. Technological opportunity and spillovers of R&D: evidence from firm's patent, profits and market value, American Economic Review 76, pp. 984-1001.
- Jones, C.I, Williams, J.C., 1998. Measuring the social return to R&D. Quarterly Journal of Economics 113 (4), pp. 1119-1135.
- Jorgenson, D.W. 2001 Information Technology and the U.S. Economy, American Economic Review, 91(1), pp.1-32.
- Jovanovic B., Rousseau P. L., 2005. General Purpose Technologies. In: Aghion, P., Durlauf, S. (Eds.), Handbook of economic growth, Elsevier, Amsterdam, vol. 1 ch. 18.

- Kiley, M.T., 2001. Computers and growth with frictions: Aggregate and disaggregate evidence. Carnegie-Rochester Conference Series on Public Policy 55, pp. 171-215.
- Kleibergen, F., Paap, R, 2006. Generalized reduced rank tests using the singular value decomposition, Journal of Econometrics 133(1), pp. 97-126,
- Lee, G., 2005. Direct versus indirect international R&D spillovers. Information Economics and Policy 17(3), pp. 334-348.
- Lipsey, R G, K I Carlaw, and C T Bekar (2005), *Economic Transformations: General Purpose Technologies and Economic Growth*, Oxford University Press
- Lipsey, R. G., Bekar, C., Carlaw, K., 1998. What requires explanation? In: E. Helpman (Ed.): General Purpose Technologies and economic growth, MIT Press, Cambridge MA.
- Moshiri, S., Simpson, W., 2011. Information technology and the changing workplace in Canada: firmlevel evidence, Industrial and Corporate Change 20(6), pp. 1601-1636.
- Mun S.-B., Nadiri, N. I. 2002. Information technology externalities: Empirical evidence from 42 U.S. industries, NBER working paper, NBER Working Paper No. 9272.
- Oliner, S.D., Sichel, E.E., Stiroh, K.J. (2008). Explaining a productive decade. Journal of Policy Modeling 30(4), 633-673.
- O'Mahony, M., Vecchi, M., 2005. Quantifying the impact of ICT capital on growth: An heterogeneous dynamic panel approach, Economica 72, pp. 615-633.
- O'Mahony, M., Vecchi, M., 2009. R&D, knowledge spillovers and company productivity performance. Research Policy 38, pp. 35-44.
- Oulton, N., 1996. Increasing returns and externalities in UK manufacturing : Myth or reality? Journal of Industrial Economics 44 (1), pp. 99-113.
- Pesaran, M.H 2006. Estimation and inference in large heterogeneous panels with a multifactor error structure, Econometrica 74(4), pp. 967-1012.
- Polder, M., van Leeuwen, G., Mohnen, P., and Raymond, W., 2010. Product, process, and organizational innovation: drivers, complementarity and productivity effects. UNU-MERIT Working Paper Series 035.
- Roodman, D. 2009. A note on the theme of too many instruments, Oxford Bulletin of Economics and Statistics 71(1), pp. 135-158.
- Romer, P. M., 1990. Endogenous technological change. Journal of Political Economy, 98, pp. S71-S102.
- Rowlatt, A., 2001. Measuring e-commerce: Developments in the United Kingdom. Economic Trends 575, pp. 30-36.
- Schankerman, M., 1981. The effect of double-counting and expensing on the measured returns to R&D. Review of Economics and Statistics 63, pp. 453-458.

- Severgnini, B. 2011. Is ICT a Jack-in-the-Box? A counterfactual approach for identifying productivity spillovers, Copenhagen Business School, mimeo.
- Stiroh, K. J., 2002. Are ICT Spillovers driving the New Economy?, Review of Income and Wealth, 48(1), pp. 33-57.
- Vandenbussche, J., Aghion, P., Meghir, C., 2006. Growth, distance to frontier and composition of human capital. Journal of Economic Growth 11(2), 97-127.
- Van Leeuwen, G., van der Wiel, H., 2003. Do ICT spillover matter: Evidence from Dutch firm-level data. CPB Discussion Paper No 26.
- Van Reenen, J., Bloom, N., Draca, M., Kretschmer, T., Sadun, R., 2010. The economic impact of ICT, Research report, SMART N. 2007/0020.
- Vecchi, M., 2000. Increasing returns versus externalities: Pro-cyclical productivity in US and Japan. Economica 67, pp. 229-244.
- Venturini, F. 2009. The long-run impact of ICT, Empirical Economics, 37(3), pp. 497-515,
- Venturini, F. 2011. The modern drivers of productivity, University of Perugia, mimeo.
- Yasar, M., 2012. Imported capital input, absorptive capacity, and firm performance: Evidence from firm-level data, Economic Inquiry, forthcoming.
- Wolff, E.N., 2011. Spillovers, linkages, and productivity growth in the US Economy, 1958 to 2007. NBER Working Papers 16864.
- Zhu, L., Jeon, B.N., 2007. International R&D spillovers: trade, FDI, and Information Technology as spillover channels. Review of International Economics 15(5), pp. 955-976.